Integrated Gait Triggered Mixed Reality and Neurophysiological Monitoring as a Framework for Next-Generation Ambulatory Stroke Rehabilitation

Li-Wei Ko, *Member, IEEE*, Cory Stevenson, Wei-Chiao Chang, Kuen-Han Yu, Kai-Chiao Chi, Yi-Jen Chen, and Chia-Hsin Chen

***Abstract*— Brain stroke affects millions of people in the world every year, with 50 to 60 percent of stroke survivors suffering from functional disabilities, for which early and sustained post-stroke rehabilitation is highly recommended. However, approximately one third of stroke patients do not receive early in hospital rehabilitation programs due to insufficient medical facilities or lack of motivation. Gait triggered mixed reality (GTMR) is a cognitive-motor dual task with multisensory feedback tailored for lower-limb post-stroke rehabilitation, which we propose as a potential method for addressing these rehabilitation challenges. Simultaneous gait and EEG data from nine stroke patients was recorded and analyzed to assess the applicability of GTMR to different stroke patients, determine any impacts of GTMR on patients, and better understand brain dynamics as stroke patients perform different rehabilitation tasks. Walking cadence improved significantly for stroke patients and lower-limb movement induced alpha band power suppression during GTMR tasks. The brain dynamics and gait performance across different severities of stroke motor deficits was also assessed; the intensity of walking induced event related desynchronization (ERD) was found to be related to motor deficits, as classified by Brunnstrom stage. In particular, stronger lower-limb movement induced ERD during GTMR rehabilitation tasks was found for patients with moderate motor deficits (Brunnstrom stage IV). This investigation demonstrates the efficacy of the GTMR paradigm for enhancing lower-limb rehabilitation, explores the neural activities of cognitive-motor tasks in different stages of stroke, and highlights the potential for joining enhanced rehabilitation and real-time neural monitoring for superior stroke rehabilitation.**

***Index Terms*— AR/VR, clinical treatment, electroencephalogram (EEG), mixed reality, motor control, lower-limb stroke rehabilitation.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Kaohsiung Medical University Chung-Ho Memorial Hospital IRB (case number: KMUHIRB-E(I)-20170020).

Li-Wei Ko, Cory Stevenson, Wei-Chiao Chang, and Kuen-Han Yu are with the Center for Intelligent Drug Systems and Smart Bio-Devices, Institute for Bioinformatics and Systems Biology, National Yang Ming Chiao Tung University (formerly National Chiao Tung University), Hsinchu 30010, Taiwan (e-mail: lwko@nctu.edu.tw).

Kai-Chiao Chi is with the Department of Occupational Therapy, Kaohsiung Medical University Hospital, Kaohsiung 807378, Taiwan, and also with the School of Medicine, College of Medicine, Kaohsiung Medical University, Kaohsiung 807378, Taiwan.

Yi-Jen Chen and Chia-Hsin Chen are with the Department of Physical Medicine and Rehabilitation, Kaohsiung Medical University Hospital, Kaohsiung 807378, Taiwan, and also with the School of Medicine, College of Medicine, Kaohsiung Medical University, Kaohsiung 807378, Taiwan (e-mail: chchen@kmu.edu.tw).

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I. Introduction

POST-STROKE rehabilitation is a long term battle, which includes many different stages and approaches throughout the course of a patient's recovery. However, many hindrances may cause stroke patients to miss proper rehabilitation, such as insufficient medical facilities, lack of motivation, transportation difficulties, or economic burden. Creative assist approaches have utilized novel technologies to transform traditional rehabilitation processes into efficient, intriguing experiences in order to raise motivation and accelerate different stages of the rehabilitation progress, such as robotic assisted systems [1]–[4], virtual reality (VR) [5]–[9], and brain-computer interfaces [4], [8]–[11]. Stroke occurs due to a blockage or reduction of blood supply in the brain, the resulting central nervous system (CNS) damage leads to motor or other functional losses. Traditional post-stroke rehabilitation therapies focus solely on behavioral outcomes even though the peripheral nervous system is usually intact in the case of brain stroke. As non-invasive brain imaging techniques, such as electroencephalography (EEG), have emerged and become more widely used, there has been an increase of attention to the importance of CNS condition and neural activity during stroke rehabilitation.

TABLE I
CLINICAL CHARACTERISTICS OF PARTICIPANTS

Patient	Age (year)	Gender (Male/Female)	Lesion Location[a]	Brunnstrom Stage (Stage V/IV/III)	Time Since Stroke (month)
A	55	Female	Right Basal Ganglion Hemorrhage	IV	18
B	46	Male	Left Basal Ganglion Hemorrhage	III	4
C	62	Male	Right Hemorrhage	IV	16
D	63	Female	Right Basal Ganglion Infraction	V	5
E	69	Female	Right MCA Infraction	IV	12
F	55	Female	Left MCA Infraction	V	1
G	39	Male	Right MCA Infraction	III	5
H	57	Male	Right Putaminal Hemorrhage	IV	3
I	51	Male	Right Basal Ganglion Hemorrhage	III	3
	55.2 ± 9.1	**5/4**	**-**	**-**	**7.3 ± 5.8**

[a] MCA = middle cerebral artery.

Conventional post-stroke rehabilitation therapy can be vitally augmented by EEG monitoring, in particular there have been various attempts to use EEG for the prevention of laziness or slacking by patients during robot assisted therapy. One such investigation tried to avoid this slacking problem by introducing EEG-based movement intention detection techniques using event-related desynchronization (ERD), which is exhibited as a drop in power of particular EEG frequencies during performance of certain tasks [12]. In another, EEG-based mental fatigue detection during stroke rehabilitation had been used to keep track of the efficacy and quality of stroke rehabilitation therapy [11]. Prognostic and monitory EEG-biomarkers during resting and task states have been identified recently to determine proper intervention timing and to predict the therapeutic efficacy of the given interventions [13]. Moreover, increasing numbers of studies have employed mobile brain/body imaging (MoBI) to investigate neural dynamics synchronized with body motion capture and other modalities of physiological significance [14]. MoBI reveals new insights into the neural dynamics of active human movement with realistic tasks outside of the laboratory and has been utilized in many kinds of neural imaging studies [15]–[17]. We have recently proposed a post-stroke lower-limb rehabilitation system [18], in the spirit of MoBI, to overcome conventional movement restrictions and comprehensively explore the neural dynamics and behavioral outcomes during active post-stroke lower-limb rehabilitation in the real world. This new imaging modality exhibits great potential for home-based post-stroke rehabilitation, by providing not only behavioral outcomes, but also neurological information to remote medical professionals.

Novel and creative rehabilitation tasks with EEG monitoring shed light on post-stroke rehabilitation by emphasizing the fundamental aspects of stroke recovery mechanisms, opening new opportunities in stroke rehabilitation therapy. Neural plasticity reorganizes and reconnects the undamaged neurons through a series of spontaneous and learning dependent processes [19], and plays a central role in stroke recovery [20]–[24]. An enriching and motivational environment promotes motor recovery and neural plasticity [25], [26]. Creating an intriguing and motivational rehabilitation scenario that not only improves rehabilitation efficacy via behavioral outcomes, but also accelerates recovery in the brain.

To provide an enhanced rehabilitation experience, we utilized the mixed-reality music rehabilitation (MR^2) system which integrates EEG monitoring, an auditory/visual augmented reality interface, and gait analysis into a platform on which the gait triggered mixed reality (GTMR) task, a dual cognitive-motor task designed as an immersive and interactive rehabilitation scenario, was deployed. This allows observation of not only the behavioral outcomes during these rehabilitative tasks, but also exploration of the associated neural dynamics. This study was intended to assess the applicability and usability of this system and task for rehabilitation across the varied capabilities of ambulatory stroke patients.

II. METHODS

A. Participants

Nine post-stroke patients were recruited for this study, five male and four female. As stroke varies in severity, the commonly used Brunnstrom Scale categorizes mobility during recovery on a I to VI scale, with spasticity and volitional control being characterized to assess the nature of the movements [27]. As our task requires volitional movement, the inclusion criteria were: (1) post-stroke patients classified in Brunnstrom Stage III, IV, or V with hemiplegia in a lower-limb, defined by volitional control of that limb with decreasing degrees of spasticity, (2) being able to complete a one-minute walk by themselves, with or without assistive devices, such as a cane, and (3) with no significant visual or aural impairments. The individual clinical characteristics of stroke patients are detailed in Table I. All experiments were practiced under Institutional Review Board (IRB) regulations and national laws. The experiment was approved by the Kaohsiung Medical University Chung-Ho Memorial Hospital IRB (case number: KMUHIRB-E(I)-20170020). All participants gave written informed consent and were given a specified description before participating in the experiments. Brunnstrom stage assessments were performed by their physical therapists before experimental participation.

B. Gait Triggered Mixed Reality (GTMR)

The GTMR task is a dual cognitive-motor task which uses a music rhythm game embedded in a real-time gait monitoring and feedback system. In our previous study [18],

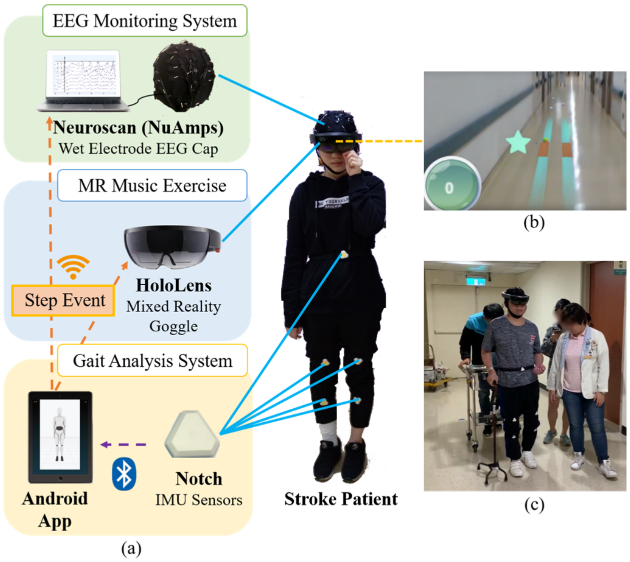

Fig. 1. (a) The system structure of the MR^2 system [18]. (b) Screen shot of the rhythm game inspired mixed reality music exercise. (c) The experimental environment of this study.

we proposed a multimodal mixed reality music rehabilitation system utilizing a gait-triggered mixed reality environment and the preliminary results showed promising potential for assisting lower-limb stroke rehabilitation. The mixed reality music rehabilitation (MR^2) system structure is illustrated in Figure 1(a). The MR^2 system is composed of three integrated systems: an EEG monitoring system, for collecting neurophysiological data, a mixed reality interface system, presenting both visual and auditory stimuli in augmented reality, and a gait analysis system, using inertial measurement units on the lower limbs. The EEG monitoring system continuously records EEG data through one subject's experimental session. The GTMR game is tailored to assist walking lower-limb stroke rehabilitation by giving the participants real-time visual feedback related to their walking gait. The contents of the music-themed rhythm game are presented as a holographic overlay on the HoloLens (Microsoft Corp.; Redmond, USA) mixed reality system. As shown in Figure 1(b), white target balls are generated alternatingly onto the left or right blue tracks according to the music beats. The target balls move towards the participants along the blue track, urging the participants to react by making a step forward on the corresponding side. When the participants make a step forward, and the step meets a predefined knee joint angle standard, the gait analysis system sends the detected step event back to the HoloLens, generating a rainbow colored bullet on the corresponding (left/right) side of the track, which moves towards the white target ball. Participants gain points when the rainbow-colored bullets impact and negate the white target balls. There were three song choices which were all trimmed to a 1-minute duration and the total number of white ball targets was adjusted to 90 (45 for each side). The target amount was designed according to the lower bound of the average for healthy elders' natural walking cadence, approximately 91.7 to 116 step/min [28]–[33]. Five inertial measurement unit (IMU)-based motion capture sensors were fastened on the lower-limbs of the participants (one at hip level and two on each leg). The gait data from the motion capture system was streamed out in real time, via Bluetooth, to the Android application on the experimenter's tablet. The step detection algorithm identifies steps by the periodic peaks of the knee angle and sends the detected step event to both music rhythm game exercise on the HoloLens and the EEG recording computer. If the knee joint angle of the step failed to pass 30° during walking, the step event would not be sent; this knee angle threshold encouraged the participants to lift their feet up, as they often fail to do so, due to post-stroke symptoms. The experimental environment and the experimental setup is shown in Figure 1(c). A video demonstration of this experiment can found at the following link: https://youtu.be/jt1qRhhvV1U.

C. Experimental Design and Data Acquisition

The experiment consisted of two experimental conditions, single task (ST) trials, where the participants walked at a natural pace, and GTMR trials, where the participants walked with the active MR^2 system. There were three phases in each trial: a standing phase, walking phase, and resting phase. At the beginning of both ST and GTMR trials, the participants were asked to stand still for a 30-second-long standing phase. The standing phase would be utilized as the baseline of each trial in later EEG analysis. After the standing phase, the participants were asked to walk at a natural pace for 1 minute in the walking phase of the ST trials. Complementarily, during the walking phase of the GTMR trials, the participants performed the 1-minute-long GTMR task wearing the MR^2 system. Finally, in the resting phase for both conditions, the participants were instructed to stop walking and stand still for 30 seconds. Behavioral and EEG data were collected throughout all of the phases of all the trials. Each participant repeated five ST trials and five GTMR trials with self-determined lengths of rest in between. The order of performing the blocks of GTMR and ST trials was randomized for each subject to eliminate fatigue as a performance factor.

The EEG data was continuously recorded at a sampling rate of 1 kHz, with a 32-channel wet electrode, Neuroscan (NuAmps) EEG recording system. The EEG data of each participant was recorded continuously for the whole session, with the impedance of the EEG signal maintained under 5 kΩ. The 32 channel locations followed the international 10-20 system. The EEG data was analyzed offline using the EEGLAB toolbox in Matlab. The gait data was recorded at 40 Hz with the Notch motion capture system. The IMU sensor calibrations were performed before each trial in order to avoid error accumulation due to gyro drift. There were five IMU-based sensors fastened on the lower-limbs of the participants, consisting of hip, right thigh, left thigh, right lower leg and left lower leg. The recorded gait dataset contained continuous joint angle data of right hip, left hip, right knee, and left knee flexion angles.

D. Gait Data Analysis

Knee joint flexion active range of motion (AROM) measures the range from the maximal knee extension angle to maximal

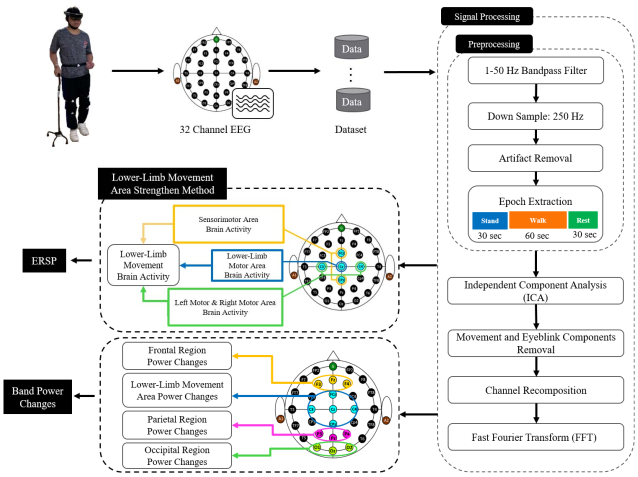

Fig. 2. A flow chart detailing the analysis processing of the electroencephalography data.

knee flexion angle in each gait cycle assessed during the walking phases. The AROM of participants' two knees were calculated individually as the hemiplegic side knee AROM and the non-hemiplegic side knee AROM, with hemiplegic side defined as the stroke-affected side. In addition to AROM, the cadence, defined as the amount of steps taken in one minute, was also assessed during the walking phase. The cadence result is the measurement of both sides combined since steps necessarily alternate.

E. EEG Data Analysis

The collected EEG data was analyzed to isolate the neural correlates of walking under the rehabilitative experimental conditions, the process for which is illustrated in Figure 2.

1) *Signal Preprocessing*

The four principal steps for the 32-channel EEG signal preprocessing included band-pass filtering, downsampling, artifact removal, and epoch extraction. A 1-50 Hz band-pass finite impulse response (FIR) filter was applied in order to avoid baseline drift, remove high-frequency ambient noise, and prepare for independent component analysis (ICA). The filtered EEG data was downsampled from 1000 to 250 Hz for efficient data analysis. As walking EEG signal is usually noisy and contaminated by large movement and muscle artifacts, two artifact removal methods, bad channel removal and artifact subspace reconstruction (ASR) [34], [35], were applied to eliminate the noise. The channels were visually inspected to identify and remove broken or atypical channels. ASR was applied to automatically remove muscle and eye blink artifacts and to reconstruct the clean EEG data. Finally, the EEG data epochs were extracted according to the experimental condition, subject, and phase. Each epoch contained a 30-second standing phase, followed by a 1-minute walking phase, and finally, a 30-second resting phase.

2) *Independent Component Analysis (ICA)*

Independent component analysis is a standard and effective method for distinguishing independent signal sources in multi-sourced linear recorded signals. ICA was applied in order to identify different signal sources (independent components) and their locations, which was practical for isolating the signals from our regions of interest or eliminating non-brain signal sources. ICLabel [36] provided by EEGLAB toolbox was employed in order to help classify the components into brain, muscle, eye, heart, channel noise, or other sources. ICLabel is a powerful tool for automatically classifying components, providing a more objective interpretation compared to traditional component classification methods. This is done by implementing a machine learning-based component classification model trained on half a million components, from more than eight thousand recordings, and labeled by numerous EEG analysis scientists. Two different component selection approaches were applied for the two parts of EEG results analysis. For the channel-based band power results, we retained the components which were classified as brain source by ICLabel, with a probability above 70%. The selected components were back-projected to the channel base for band power analysis in different regions. A relatively strict component selection criteria was implemented for the sensorimotor area time-frequency results since we wanted to closely inspect the walking movement related to brain oscillations. In this component selection approach, the selecting criteria for the retained components were as follows: (1) the component was classified as brain source by ICLabel, (2) was close to the brain area associated with lower-limb movement, and (3) at least 2 components were selected for each subject. These selection criteria ensured the EEG analysis signal were brain sourced, lower-limb movement related, and not dominated by only one component. The selected components were also back-projected to the channel base for time-frequency analysis in the sensorimotor areas.

3) *Fast Fourier Transform (FFT)*

Fast Fourier Transform (FFT) was applied to the back-projected EEG data in both band power analysis and sensorimotor area time-frequency analysis in order to transform the time domain EEG data to frequency and time-power-frequency domains. The FFT for band power analysis was executed using a hamming window, with a size of 2 seconds and a 50% overlap. The FFT frequency range was set from 1 to 50 Hz.

4) *Time-Frequency and Band Power Analyses*

Two analysis approaches were used in this study. The time-frequency analysis was used to closely observe the brain dynamics in the lower-limb movement area of the brain and the band power analysis was used to observe the brain dynamic in different brain regions. Time-frequency analysis provides not only the frequency, but also the temporal information of the EEG data, which allows us to observe both stationary and non-stationary phenomena. Event-related spectral perturbation (ERSP) was employed to visualize the time-frequency results. Both band power and time-frequency results were baseline normalized in each trial to the corresponding standing phase EEG data. In order to target the brain dynamics of the lower-limb movement areas, a lower-limb movement area strengthening method was applied to the back-projected channel data near the sensorimotor area. Based on the brain anatomy, the Cz channel is the nearest to the lower-limb movement area, the FCz channel and the CPz channel, which are proximal to Cz, were averaged to into the ERSP results. Channel C3 and C4 were also averaged into an ERSP result. Finally, these two averaged ERSP results and Cz channel ERSP result were averaged, as illustrated in Fig. 2. This lower-limb movement area strengthening method was performed to strengthen the signal from the channels nearest to the lower-limb movement area.

F. Statistical Analysis

After processing, both gait and EEG data were assessed statistically to determine significant effects of the GTMR task. Due to the small numbers of trials and subjects ($n = 9$) and the high variability between subjects the distributions could not be determined to be normal, particularly when the patient pool was divided into particular Brunnstrom stages. Therefore, the non-parametric Wilcoxon signed-rank test was used to compare between conditions, as it does not assume such distributions. A significance threshold of 0.05 was used. Due to the small number of subjects in each group, individual subject data is displayed to allow for more particular.

III. Results

A. Gait Performance

One of the primary objectives of the GTMR task is to improve subject's walking quality. Improvement in walking can be assessed for both temporal and spatial features, utilizing kinematic sensors attached to the legs. Improvements in timing were assessed by measuring cadence, the number of steps taken per minute, during the 60 second walking portion of the experiment. A significant increase in cadence during GTMR trials was observed, increasing to an average of 82.2 steps/min, from an average of 74.1 steps/min in the ST trials (Figure 3). Individually, almost all of the patients exhibited the same or better average cadences, however this improvement was highly variable (Fig. 4). Statistically significant improvement occurred in the stage IV patients, which increased from a group average of 76.1 steps/min to 89.5 steps/min, near the target cadence of 90 steps/min, though notably this is driven by large increases by subjects C and E. Neither stage III or V, showed such statistical improvements at the group level.

In addition to the metric of cadence, the quality of the steps taken was assessed using the kinematics of the leg. As a common deficit in post-stroke patients is hemiplegia resulting in foot dragging, one of the design parameters of the GTMR task was to promote patients to lift their feet. From the sensors placed on the body, the flexion angle of each knee joint during the progress of each step could be determined, within a possible range from 0°, with a straight leg at standing, to 90°, with the knee at a right angle. The quality

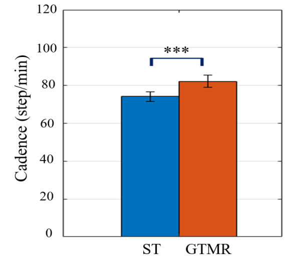

Fig. 3. The average cadence of stroke patients during ST and GTMR tasks. A significant cadence growth was observed during the GTMR trials. The p-value of Wilcoxon signed rank test shows the significant difference ($p < .001$).

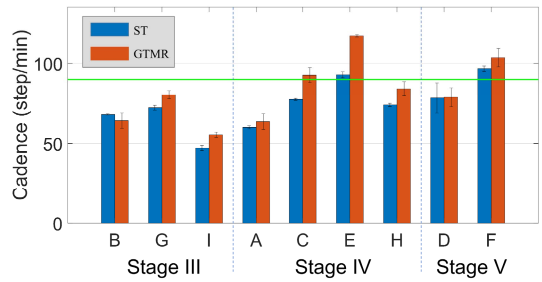

Fig. 4. The average cadence of individual stroke patients in different Brunnstrom stages during ST and GTMR tasks. Some cadence improvement during GTMR trials was exhibited in almost all patients. The error bars represent the standard deviation across the trials for that condition. A statistically significant cadence increase at the group level was observed only in stage IV. The green line indicates the 90 steps/min cadence goal of the GTMR task.

of the step was assessed by knee active range of motion (AROM), the peak knee flexion angle during the progress of a step. While the GTMR task did not produce statistically significant changes in knee flexion AROM across the entire population, the AROM for the hemiplegic knee did increase in the Brunnstrom Stage IV group (Figure 5). While no changes were seen in the Stage V group, a slight decrease in AROM in both hemiplegic and non-hemiplegic knees was seen in the Stage III group, for the GTMR tasks, relative to the ST tasks.

B. Neural Response

Neural responses during the walking tasks were recorded using EEG. Analysis of the ERSP of the EEG signals allows for interpretation of the power changes in different frequency components over the time course of the walking tasks (Figure 6). From this analysis it can be seen that during the walking tasks all subjects showed a typical alpha (8-12 Hz) band power suppression relative to the standing phases of each trial. This alpha band suppression was present for all subjects under both conditions, however the extent of the suppression varied significantly depending on the severity of the stroke, with lower Brunnstrom stages displaying lower amounts of alpha suppression. Brunnstrom stage V patients exhibited alpha suppression levels to the most significant extent, stage III patents showing minimal suppression, and stage IV showing a clear intermediate level between the two. While particular subjects showed increased central alpha suppression in the ERSPs of the GTMR task relative to the ST task, the statistical

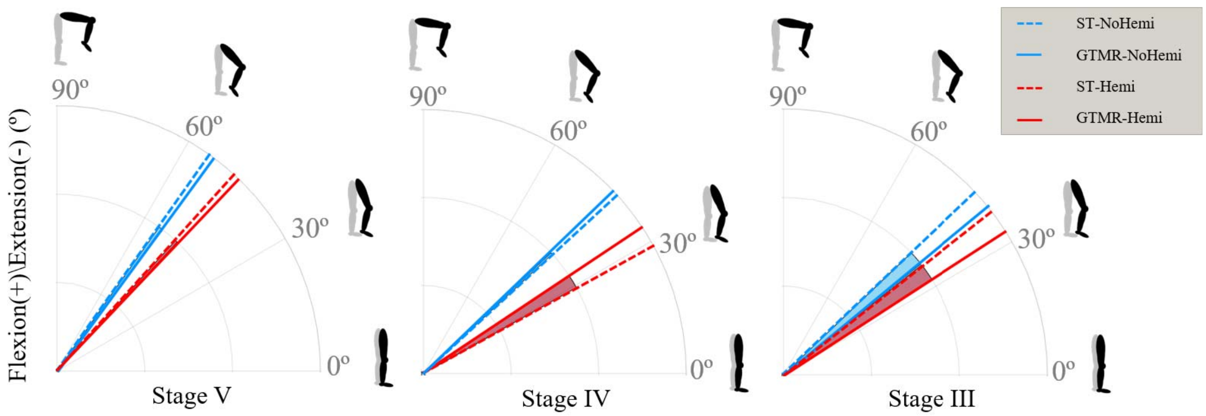

Fig. 5. The average active range of motion (AROM) of knee flexion for stroke patients at different Brunnstrom stages. Knee flexion AROM increased during GTMR trials for Brunnstrom stage IV patients while knee flexion AROM of Brunnstrom stage III patients dropped. No significance was found in the knee flexion AROM between ST and GTMR trials (using of Wilcoxon signed rank test). (Hemi = hemiplegic, NoHemi = non-hemiplegic).

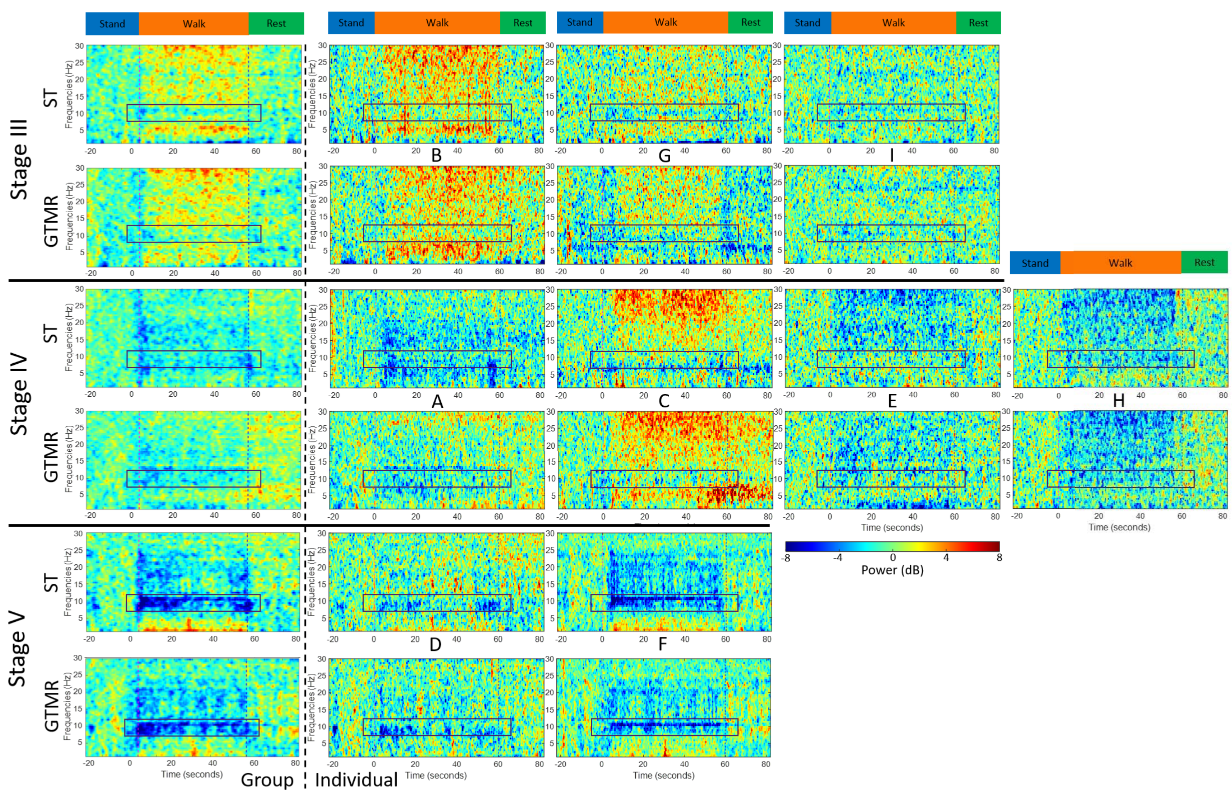

Fig. 6. Event related spectral perturbations (ERSPs) in the sensorimotor cortices of gait triggered mixed reality (GTMR) and single task (ST) trials for stroke patients at different Brunnstrom stages, showing the group level composites (left column) and the individual subjects within that group. Walking-induced ERD in the alpha bands (8-12 Hz) during GTMR and ST trials can be seen in all stages (highlighted regions). The baseline used was before time t = 0 s corresponding to the standing phase preceding the dotted red line. The end of the walking phase and is demarked by a dotted blue line at t = 60 s.

strength of these differences was not able to be established at the group level.

A closer analysis of spectral power in different regions of the brain revealed differences in activations between the GTMR and ST conditions in different groups. During the GTMR task, stage IV patients displayed significantly increased power in the theta (4-7 Hz) and low-gamma (13-24 Hz) frequency bands across most medial regions of the cortex, including the medial-frontal cortex, along with increased power in all frequency bands in the parietal region (Figure 7). Outside of stage IV patents, minimal power differences between tasks was seen in Brunnstrom stage V and stage III patients at the group level.

IV. Discussion

In this study, the GTMR task was utilized as a cognitive-motor dual task tailored to assist lower-limb post-stroke rehabilitation. The experiment was designed to investigate the

Fig. 7. Comparison of each subject's spectral power of ST and GTMR conditions in theta (4-7Hz), alpha (8-12Hz), beta (13-24Hz), and low-gamma bands (25-40Hz) at different cortical locations. Subjects are grouped into Brunnstrom stages (Stage III: B, G, I; Stage IV: A, C, E, H; Stage V: D, F). Power increases in theta bands near frontal regions and increases of low-gamma bands near frontal, central and parietal regions can be observed in Brunnstrom stage IV. Decreases in gamma band power near parietal and occipital can be seen in Stage III.

neural dynamics of stroke patients during these assisted lower-limb rehabilitation tasks. Behavioral and EEG measurements and analyses were carried out in order to assess the applicability and usefulness of the GTMR task for rehabilitation and observe the brain dynamics of unassisted and GTMR assisted walking.

A. Improving Rehabilitation With Gait Triggered Mixed Reality

Compared to traditional single task lower-limb stroke rehabilitation (only walking), research has increasingly suggested that cognitive-motor dual tasks not only improve walking ability [37]–[39] and reduce fall risk [38], but also enhance brain activation [40], [41] in stroke patients. The GTMR task employed in this study was designed based on similar principles, and improved cadence as compared to the ST trials. However, the source of much of this cadence increase was derived from larger improvements in the Brunnstrom Stage IV group, the Stage III and V patients didn't show significant cadence improvements. Some of this discrepancy could be traced to the designed task difficulty, which was calibrated to a healthy target cadence of 90 steps/min. Stage V patients performed ST walking near this rate already, therefore it could be expected that no significant difference between GTMR and ST tasks would be found. As the experiment was designed not just for speed, but to encourage patients to lift their feet, instead of dragging them, this logic is also represented in the AROM results, where there was negligible difference between leg movements between the two tasks and the angles between hemiplegic and non-hemiplegic legs are similar in Stage V. The difference in Stage IV and Stage III improvements, for both cadence and AROM results, can also be interpreted similarly. Stage IV subjects were capable of achieving the objectives of the task, but the task was either too ambitious or difficult for the Stage III subjects. Stage IV subjects showed significant improvements during the GTMR task when compared to standard walking, in both cadence, which approached the ideal, and in hemiplegic knee AROM. Unfortunately, the Stage III subjects did not show improvements, and actually displayed nominally decreased AROM angles for both legs in the GTMR task. This discrepancy is suspected to be an influence of cognitive motor interference, which is common for dual task rehabilitation, particularly with the fact that it is exhibited in both legs. Such cognitive motor interference has been identified in reduction of gait performance during other dual-task walking experiments [42]–[44].

One of the objectives of this study was to assess the applicability of this system and task across stages. Given the small sizes of the patient groups, limited statistical power is a problem, and therefore strong conclusions based on group level statistics are difficult to ascertain. However, the applicability of the task across the population can still be gleaned, based upon what group level findings are available and the trends seen across the individual subjects. Overall the heterogeneity of the different individuals and stages is apparent, and indicates a fundamental challenge for improvements of any rehabilitation system must incorporate, that training with an appropriate intensity and motivation is essential for effective post stroke rehabilitation. Luckily game-based rehabilitation tasks, like GTMR, can easily alter task difficulty by toning down the density of music beat targets, changing songs or virtual cues, and widening acceptable tolerances. Beyond allowing the therapy difficulty to be set appropriately, such a system allows for an actively adaptive task, dynamically adjusting the difficulty and environment to their particular level, as to continually challenge and engage the subject, but without making the task unachievable or demoralizing the subject. This could even be done specifically to focus on where the particular deficits of a subject, for example reinforcing improper leg kinematics, even if the subject is performing well in speed.

B. Cortex Oscillations in Recovering Stroke Patients

As the recovery that occurs during rehabilitation is reflective of neural changes due to neural plasticity, the impact of rehabilitation scenarios should be present in the processes of brain and the signals they generate. The multisensory feedback endemic to the GTMR task creates an intensive and motivational rehabilitation environment, the effects of which were assessed electrophysiologically. Decreases in power of central alpha were shown in both GTMR and ST walking tasks. Similar decreases in alpha and beta bands over sensorimotor cortices has been found during active walking on the treadmill, where it has been suggested that these decreases are related to increased cortical involvement during active and/or spontaneous lower-limb movement [45]–[47]. Unfortunately, there was not sufficient statistical differences in central alpha power between the GTMR and ST tasks at the group level, though there were notable statistical differences for certain individuals. The inability to robustly resolve these differences at the group level are likely a result of lack of statistical strength due to small numbers of subjects within each group and heterogeneity of brain lesion locations throughout the subject pool. Despite not being able to resolve differences in ERDs between tasks, clear differences in central alpha depression during walking was present across different stages of stroke, with a better stroke progression corresponding to stronger ERD. This is in line with evidence showing that EEG-based analyses, such as quantitative electroencephalography, which derives quantitative metrics, such as power spectra, from EEG signal, can serve as prognostic indices and monitory biomarkers in post-stroke motor recovery [13], [48]–[51]. There has been multiple investigations correlating cortical parameters and stroke disability assessment scales, such as the National Institutes of Health Stroke Scale (NIHSS) [48], [49], activity of daily living (ADL) evaluations [52], modified Rankin Scale (mRS) [51], and Fugl-Meyer assessments (FMA) [13], [50], [51], [53].

Investigating GTMR effects in other regions of the brain did yield some statistically relevant differences between the GTMR and ST conditions, showing the impact of the GTMR task on the brain and indicating where the most benefit may be derived. Studies have linked low frequency band power increases with task difficulty [54] and decision making [55]. Gevins *et al.* reported that difficult tasks elicited large theta signals at AFz (midline of Fz and FPz channel) [54], which may indicate that the relative increases of frontal theta seen in many subjects in our study are indicative of the challenge of the GTMR task. In accordance with previous studies comparing active to passive walking [45], [46], we observed significant power increases in low gamma band frequencies (25-40Hz) at frontal, central, and parietal regions during GTMR trials of the stage IV patients. Similarly, Bulea *et al.* observed significant increases in gamma band frequencies over the posterior parietal cortex during active treadmill walking when compared to passive walking [45]; such gamma increases in our study may indicate that our virtual task helps drive motor processes in a similar way to a physical external driver. We also observed broadband power increases near the parietal area for stage IV patients, analogous to results by Chang *et al.* [56], who observed similar broad band power increases at Pz and Oz channels during VR balancing tasks for elders with fall risk. Notably, the most significant neural effects were seen in the stage IV subjects, who also exhibited the strongest improvement in cadence during the GTMR trials. This indicates that the use of the GTMR as a rehabilitation tool, was most effective for and most accurate to the capabilities of the stage IV subjects, and that such EEG features correspond to task effectiveness. If the task presented by the GTMR was too easy, then minimal differences in neural response indicating challenge would be expected, as exhibited in the stage V subjects. Stage III subjects displayed possible decreases in cortical power during the GTMR tasks, relative to the ST tasks, however the robustness of this was limited by sample size, this could indicate that these subjects found both normal walking and that enhanced with GTMR equally challenging, or that the GTMR task was felt to be too difficult and subjects became apathetic. These results indicate that the GTMR task is an effective challenge and engaging method of therapy for rehabilitation and again reiterate the need to customize the task and adapt its difficulty to the varied capabilities of the participants.

C. Towards Home Based Rehabilitation

While this study assessed the immediate neurological and behavioral effects of the GTMR task, showing its capabilities as part of a potential rehabilitation regime, further assessment in a longitudinal study is needed to address its efficacy for long term rehabilitation and how it compares to traditional rehabilitation systems. Given its small sample size and focus on determining the applicability across the range of physiological capabilities in ambulatory stroke patients, this study is limited to this assessing the applicability to particular subjects and acting as a guide for continued studies which can focus on the particular impact that it has on a more targeted population. Further work is also needed to develop an adaptive paradigm which can scale the difficulty of the task to complement capabilities of the patient and their progression through the rehabilitation progress. A notable advantage of such an automated, adaptive system is that such a system can be used at home, in conjunction with in-clinic support. Compared to traditional hospital based rehabilitation programs, home based rehabilitation offers better accessibility to medical rehabilitative care by providing cost-efficient and effective rehabilitation tasks using assist systems. Many unique features and advantages contribute to the feasibility of GTMR thriving as a practical home based rehabilitation system for assisting lower-limb stroke rehabilitation. Mixed reality based systems integrated with motion sensors can minimize the safety issues by allowing the participants to see the real-world environment. Gait triggered mixed reality provides appropriate motivation and flexibility in altering task difficulty for the different capability levels of patient. Moreover, an integrated multimodal monitoring system provides not only behavioral, but also cortical information regarding the rehabilitation progress, which can automatically be sent to supervising clinicians and rehabilitation specialists for review. Particularly, integrated EEG monitoring plays a role in stroke rehabilitation by providing CNS recovery information for tracking recovery progress comprehensively. The impacts of such a system are clearly limited to patients who are ambulatory, while such an augmented reality system could theoretically be adapted for other motor deficits, such an application would still remain limited to relatively moderate deficits where subjects can initiate and perform movements without the need for external physical interaction. Such an assisted system could potentially be integrated with exoskeletal system, which could expand the applicability to greater deficits. Such automated systems have value in expanding the potential reach of clinical rehabilitation, augmenting limited in-person capacity of facilities and staff with remotely monitored and easily accessible rehabilitation. While a wet, wired electrode EEG system was used in this study, the potential of dry, wireless electrode EEG monitoring systems as effective alternatives should be recognized for the portability and ease-of-use needed in home based rehabilitation systems. Such advancements in noninvasive brain monitoring technologies, like electroencephalography, lower the bar for in-home neurological explorations of rehabilitation for stroke. As neurological monitoring systems progress further towards commercialization and integrate with appropriate rehabilitation assist systems, like our GRMR task, emerge, home-based post-stroke rehabilitation becomes closer to providing a missing piece of the puzzle for proper and comprehensive neural rehabilitation.

V. Conclusion

In this study, we proposed a gait triggered mixed reality system tailored for assisting post-stroke lower-limb rehabilitation and assessed its application across ambulatory stroke patients. The improvement in metrics of cadence and knee AROM highlight the importance of appropriate task difficulty in lower-limb stroke rehabilitation and the capacities of such intervention. Moreover, the relationship between neural oscillations across the cortex and Brunnstrom stage provides insight into the complex neural activity of stroke patient recovery and the heterogeneity of brain activity across patients at different stages of improvement. Ultimately, gait triggered mixed reality elevates the performance of lower-limb stroke rehabilitation in a motivational environment and has the potential to significantly enhance home-based lower-limb stroke rehabilitation.

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References

[1] N. Singh, M. Saini, S. Anand, N. Kumar, M. V. P. Srivastava, and A. Mehndiratta, "Robotic exoskeleton for wrist and fingers joint in post-stroke neuro-rehabilitation for low-resource settings," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 12, pp. 2369–2377, Dec. 2019.

[2] A. S. Ciullo *et al.*, "A novel soft robotic supernumerary hand for severely affected stroke patients," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 5, pp. 1168–1177, May 2020.

[3] S. L. Norman, M. Dennison, E. Wolbrecht, S. C. Cramer, R. Srinivasan, and D. J. Reinkensmeyer, "Movement anticipation and EEG: Implications for BCI-contingent robot therapy," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 8, pp. 911–919, Aug. 2016.

[4] J.-H. Jeong, K.-H. Shim, D.-J. Kim, and S.-W. Lee, "Brain-controlled robotic arm system based on multi-directional CNN-BiLSTM network using EEG signals," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 5, pp. 1226–1238, May 2020.

[5] P. Dias *et al.*, "Using virtual reality to increase motivation in poststroke rehabilitation," *IEEE Comput. Graph. Appl.*, vol. 39, no. 1, pp. 64–70, Jan. 2019.

[6] D. Solanki and U. Lahiri, "Adaptive treadmill-assisted virtual reality-based gait rehabilitation for post-stroke physical reconditioning—A feasibility study in low-resource settings," *IEEE Access*, vol. 8, pp. 88830–88843, 2020.

[7] L. Y. Liu, S. Sangani, K. K. Patterson, J. Fung, and A. Lamontagne, "Real-time avatar-based feedback to enhance the symmetry of spatiotemporal parameters after stroke: Instantaneous effects of different avatar views," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 878–887, Apr. 2020.

[8] A. Vourvopoulos and S. B. I. Badia, "Motor priming in virtual reality can augment motor-imagery training efficacy in restorative brain-computer interaction: A within-subject analysis," *J. Neuroeng. Rehabil.*, vol. 13, no. 1, pp. 1–14, Dec. 2016.

[9] S. B. I. Badia, A. G. Morgade, H. Samaha, and P. F. M. J. Verschure, "Using a hybrid brain computer interface and virtual reality system to monitor and promote cortical reorganization through motor activity and motor imagery training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 2, pp. 174–181, Mar. 2013.

[10] M. A. Romero-Laiseca *et al.*, "A low-cost lower-limb brain-machine interface triggered by pedaling motor imagery for post-stroke patients rehabilitation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 988–996, Apr. 2020.

[11] R. Foong *et al.*, "Assessment of the efficacy of EEG-based MI-BCI with visual feedback and EEG correlates of mental fatigue for upper-limb stroke rehabilitation," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 3, pp. 786–795, Mar. 2020.

[12] E. Formaggio *et al.*, "Modulation of event-related desynchronization in robot-assisted hand performance: Brain oscillatory changes in active, passive and imagined movements," *J. Neuroeng. Rehabil.*, vol. 10, no. 1, p. 24, Feb. 2013.

[13] R. Mane *et al.*, "Prognostic and monitory EEG-biomarkers for BCI upper-limb stroke rehabilitation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 8, pp. 1654–1664, Aug. 2019.

[14] K. Gramann *et al.*, "Cognition in action: Imaging brain/body dynamics in mobile humans," *Rev. Neurosci.*, vol. 22, no. 6, pp. 593–608, 2011.

[15] P. De Sanctis, J. S. Butler, B. R. Malcolm, and J. J. Foxe, "Recalibration of inhibitory control systems during walking-related dual-task interference: A mobile brain-body imaging (MOBI) study," *NeuroImage*, vol. 94, pp. 55–64, Jul. 2014.

[16] J. A. Brantley, T. P. Luu, S. Nakagome, F. Zhu, and J. L. Contreras-Vidal, "Full body mobile brain-body imaging data during unconstrained locomotion on stairs, ramps, and level ground," *Scientific Data*, vol. 5, no. 1, Dec. 2018, Art. no. 180133.

[17] Z. Djebbara, L. B. Fich, and K. Gramann, "Understanding perceptual experience of art using Mobile brain/body imaging," in *Brain Art*. New York, NY, USA: Springer, 2019, pp. 265–282, doi: 10.1007/978-3-030-14323-7_9.

[18] W. Chang *et al.*, "EEG analysis of mixed-reality music rehabilitation system for post-stroke lower limb therapy," *J. SoC. Inf. Display*, vol. 27, no. 6, pp. 372–380, Jun. 2019.

[19] G. Kwakkel, B. Kollen, and E. Lindeman, "Understanding the pattern of functional recovery after stroke: Facts and theories," *Restorative Neurol. Neurosci.*, vol. 22, nos. 3–5, pp. 281–299, 2004.

[20] B. B. Johansson, "Current trends in stroke rehabilitation. A review with focus on brain plasticity," *Acta Neurol. Scandinavica*, vol. 123, no. 3, pp. 147–159, 2011.

[21] P. Talelli, R. J. Greenwood, and J. C. Rothwell, "Arm function after stroke: Neurophysiological correlates and recovery mechanisms assessed by transcranial magnetic stimulation," *Clin. Neurophysiol.*, vol. 117, no. 8, pp. 1641–1659, Aug. 2006.

[22] J. A. Kleim and T. A. Jones, "Principles of experience-dependent neural plasticity: Implications for rehabilitation after brain damage," *J. Speech, Lang., Hearing Res.*, vol. 51, no. 1, Feb. 2008.

[23] N. Takeuchi and S.-I. Izumi, "Rehabilitation with poststroke motor recovery: A review with a focus on neural plasticity," *Stroke Res. Treatment*, vol. 2013, pp. 1–13, Apr. 2013.

[24] J. Dąbrowski *et al.*, "Brain functional reserve in the context of neuroplasticity after stroke," *Neural Plasticity*, vol. 2019, pp. 1–10, Feb. 2019.

[25] J. Biernaskie and D. Corbett, "Enriched rehabilitative training promotes improved forelimb motor function and enhanced dendritic growth after focal ischemic injury," *J. Neurosci.*, vol. 21, no. 14, pp. 5272–5280, Jul. 2001.

[26] J. Nithianantharajah and A. J. Hannan, "Enriched environments, experience-dependent plasticity and disorders of the nervous system," *Nature Rev. Neurosci.*, vol. 7, no. 9, pp. 697–709, Sep. 2006.

[27] S. Brunnstrom, "Motor testing procedures in hemiplegia: Based on sequential recovery stages," *Phys. Therapy*, vol. 46, no. 4, pp. 357–375, Apr. 1966.

[28] R. J. Elble, S. S. Thomas, C. Higgins, and J. Colliver, "Stride-dependent changes in gait of older people," *J. Neurol.*, vol. 238, no. 1, pp. 1–5, Apr. 1991.

[29] J. O. JudgeRoy, B. Davis, and S. Ounpuu, "Step length reductions in advanced age: The role of ankle and hip kinetics," *J. Gerontol. A, Biol. Sci. Med. Sci.*, vol. 51A, no. 6, pp. M303–M312, Nov. 1996.

[30] H. Sadeghi, P. Allard, F. Prince, and H. Labelle, "Balance control and propulsion in gait of healthy young and elderly subjects," *Hip*, vol. 37, nos. 11–17, pp. 12–62, 2003.

[31] H. B. Menz, S. R. Lord, and R. C. Fitzpatrick, "Age-related differences in walking stability," *Age Ageing*, vol. 32, no. 2, pp. 137–142, Mar. 2003.

[32] M. B. van Iersel, R. P. C. Kessels, B. R. Bloem, A. L. M. Verbeek, and M. G. O. Rikkert, "Executive functions are associated with gait and balance in community-living elderly people," *J. Gerontol., A*, vol. 63, no. 12, pp. 1344–1349, 2008.

[33] A. Trombetti, M. Hars, F. R. Herrmann, R. W. Kressig, S. Ferrari, and R. Rizzoli, "Effect of music-based multitask training on gait, balance, and fall risk in elderly people: A randomized controlled trial," *Arch. Internal Med.*, vol. 171, no. 6, pp. 525–533, Mar. 2011.

[34] T. R. Mullen *et al.*, "Real-time neuroimaging and cognitive monitoring using wearable dry EEG," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 11, pp. 2553–2567, Nov. 2015.

[35] C. Chang, S. Hsu, L. Pion-Tonachini, and T. Jung, "Evaluation of artifact subspace reconstruction for automatic artifact components removal in multi-channel EEG recordings," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 4, pp. 1114–1121, Jul. 2019.

[36] L. Pion-Tonachini, K. Kreutz-Delgado, and S. Makeig, "ICLabel: An automated electroencephalographic independent component classifier, dataset, and website," *NeuroImage*, vol. 198, pp. 181–197, Sep. 2019.

[37] Y.-R. Yang, R.-Y. Wang, Y.-C. Chen, and M.-J. Kao, "Dual-task exercise improves walking ability in chronic stroke: A randomized controlled trial," *Arch. Phys. Med. Rehabil.*, vol. 88, no. 10, pp. 1236–1240, Oct. 2007.

[38] M. Y. C. Pang, L. Yang, H. Ouyang, F. M. H. Lam, M. Huang, and D. A. Jehu, "Dual-task exercise reduces cognitive-motor interference in walking and falls after stroke: A randomized controlled study," *Stroke*, vol. 49, no. 12, pp. 2990–2998, Dec. 2018.

[39] Y.-C. Liu, Y.-R. Yang, Y.-A. Tsai, and R.-Y. Wang, "Cognitive and motor dual task gait training improve dual task gait performance after stroke—A randomized controlled pilot trial," *Sci. Rep.*, vol. 7, no. 1, pp. 1–8, Dec. 2017.

[40] E. Al-Yahya, H. Johansen-Berg, U. Kischka, M. Zarei, J. Cockburn, and H. Dawes, "Prefrontal cortex activation while walking under dual-task conditions in stroke: A multimodal imaging study," *Neurorehabil. Neural Repair*, vol. 30, no. 6, pp. 591–599, Jul. 2016.

[41] Y.-C. Liu, Y.-R. Yang, Y.-A. Tsai, R.-Y. Wang, and C.-F. Lu, "Brain activation and gait alteration during cognitive and motor dual task walking in stroke—A functional near-infrared spectroscopy study," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 12, pp. 2416–2423, Dec. 2018.

[42] J.-H. Shin *et al.*, "Dual task interference while walking in chronic stroke survivors," *Phys. Therapy Rehabil. Sci.*, vol. 6, no. 3, pp. 134–139, Sep. 2017.

[43] B. Abernethy, "Dual-task methodology and motor skills research: Some applications and methodological constraints," *J. Hum. Movement Stud.*, vol. 14, no. 3, pp. 101–132, 1988.

[44] E. Al-Yahya, H. Dawes, L. Smith, A. Dennis, K. Howells, and J. Cockburn, "Cognitive motor interference while walking: A systematic review and meta-analysis," *Neurosci. Biobehavioral Rev.*, vol. 35, no. 3, pp. 715–728, Jan. 2011.

[45] T. C. Bulea, J. Kim, D. L. Damiano, C. J. Stanley, and H.-S. Park, "Prefrontal, posterior parietal and sensorimotor network activity underlying speed control during walking," *Frontiers Hum. Neurosci.*, vol. 9, p. 247, May 2015.

[46] T. P. Luu, S. Nakagome, Y. He, and J. L. Contreras-Vidal, "Real-time EEG-based brain-computer interface to a virtual avatar enhances cortical involvement in human treadmill walking," *Sci. Rep.*, vol. 7, no. 1, pp. 1–12, Dec. 2017.

[47] J. Wagner, T. Solis-Escalante, P. Grieshofer, C. Neuper, G. Müller-Putz, and R. Scherer, "Level of participation in robotic-assisted treadmill walking modulates midline sensorimotor EEG rhythms in able-bodied subjects," *NeuroImage*, vol. 63, no. 3, pp. 1203–1211, 2012.

[48] S. P. Finnigan, M. Walsh, S. E. Rose, and J. B. Chalk, "Quantitative EEG indices of sub-acute ischaemic stroke correlate with clinical outcomes," *Clin. Neurophysiol.*, vol. 118, no. 11, pp. 2525–2532, Nov. 2007.

[49] S. P. Finnigan *et al.*, "Correlation of quantitative EEG in acute ischemic stroke with 30-day NIHSS score: Comparison with diffusion and perfusion MRI," *Stroke*, vol. 35, no. 4, pp. 899–903, Apr. 2004.

[50] P. Trujillo *et al.*, "Quantitative EEG for predicting upper limb motor recovery in chronic stroke robot-assisted rehabilitation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 7, pp. 1058–1067, Jul. 2017.

[51] R. V. A. Sheorajpanday, G. Nagels, A. J. T. M. Weeren, M. J. A. M. van Putten, and P. P. De Deyn, "Quantitative EEG in ischemic stroke: Correlation with functional status after 6 months," *Clin. Neurophysiol.*, vol. 122, no. 5, pp. 874–883, May 2011.

[52] T. Yuasa, A. Maeda, S. Higuchi, and Y. Motohashi, "Quantitative EEG data and comprehensive ADL (activities of daily living) evaluation of stroke survivors residing in the community," *J. Physiol. Anthropol. Appl. Hum. Sci.*, vol. 20, no. 1, pp. 37–41, 2001.

[53] N. Riahi, V. A. Vakorin, and C. Menon, "Estimating Fugl-Meyer upper extremity motor score from functional-connectivity measures," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 860–868, Apr. 2020.

[54] A. Gevins, M. E. Smith, L. McEvoy, and D. Yu, "High-resolution EEG mapping of cortical activation related to working memory: Effects of task difficulty, type of processing, and practice," *Cerebral Cortex*, vol. 7, no. 4, pp. 374–385, Jun. 1997.

[55] J. Jacobs, G. Hwang, T. Curran, and M. J. Kahana, "EEG oscillations and recognition memory: Theta correlates of memory retrieval and decision making," *NeuroImage*, vol. 32, no. 2, pp. 978–987, Aug. 2006.

[56] C.-J. Chang, T.-F. Yang, S.-W. Yang, and J.-S. Chern, "Cortical modulation of motor control biofeedback among the elderly with high fall risk during a posture perturbation task with augmented reality," *Frontiers Aging Neurosci.*, vol. 8, p. 80, Apr. 2016.